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Research Article

Eye-Tracking as an Indicator of Depressive Emotional States in Virtual Reality: An Explainable Artificial Intelligence Approach

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***Abstract* –** This study explores the intricate relationship between eye-tracking metrics and emotional states, with a particular focus on depressive emotions, including sadness, depression, and boredom. Leveraging the VR Eyes: Emotions Dataset (VREED), a publicly available dataset that captures eye-tracking data from participants immersed in 360-degree virtual environments, we examined key eye-movement features such as saccades, micro-saccades, fixations, and blinks. By applying the Circumplex Model of Affect (CMA), we categorize emotional states along dimensions of arousal and valence, facilitating a nuanced analysis of affective responses. An Extra Trees Classifier was employed as our primary machine learning model to predict emotional states based on eye-tracking metrics, and we used Explainable Artificial Intelligence (XAI) techniques to interpret the model's decisions. These XAI techniques, such as SHAP, reveal the individual contributions of each feature, highlighting the critical role of micro-saccades and fixations as predictors of depressive states. Our findings suggest that eye-tracking metrics may serve as objective indicators of emotional experiences. This research underscores the potential of integrating eye-tracking data and machine learning within virtual environments as a valuable approach for advancing emotional assessment in mental health contexts.

Keywords – Emotion Recognition, Eye-Tracking, Explainable Artificial Intelligence, Shap, Interpretability.

I. INTRODUCTION

Emotions are associated with temporary physiological changes in the body, influenced by cognitive processes and emotional reactions. The ability to accurately identify and interpret these emotional states is essential across numerous fields, including psychology [1], physiology [2], healthcare [3], safe driving [4], education [5], and marketing [6]. Emotions such as depression and sadness affect millions globally and are leading causes of disability, often presenting with complex and subtle behavioral indicators. Traditional clinical assessments may miss nonverbal and physiological signals that reflect depressive or sad states, as individuals may consciously or unconsciously conceal their symptoms. Identifying depressive cues through objective markers such as eye-tracking metrics provides a more comprehensive understanding of an individual's emotional state beyond verbal reports. The limitation in accurately detecting depressive or sad states highlights the need for precise methods to identify and address depressive symptoms, supporting more accurate and sensitive health interventions.

Affective disorders like depression are often marked by attentional biases toward emotional stimuli [7]. Attentional bias refers to the tendency of an individual to pay more attention to certain types of information or stimuli over others. Eye-tracking measures serve as important indicators for identifying these attentional biases. Armstrong et al. [7] indicates that depressed individuals display a greater tendency to maintain their gaze on sad or negative stimuli causing longer fixation duration. Gao et al. [8] showed in their research that the fixation duration and number of fixations are significantly more in depressed individuals towards the negative stimuli. Individuals with depression tend to show a negative attentional bias toward emotional stimuli, and metrics like fixation duration and number of fixations can serve as additional objective indicators for screening depression. Zhang et al. [9] found that individuals with depression exhibited atypical eye movement patterns, specifically showing reduced saccade amplitude, shorter scan path length, and decreased saccade velocity. Li et al. [10] detected fewer saccades and longer fixation duration in depressive states.

Recent advancements in machine learning (ML) and deep learning have greatly advanced the field of emotion recognition, enabling the development of sophisticated algorithms that can analyze and interpret complex, multi-source data to infer and categorize human emotions. These classification techniques are particularly valuable, as they adhere to established theoretical frameworks for emotion, allowing for systematic categorization of affective states. By aligning with these foundational models, ML and deep learning technologies contribute not only to a deeper understanding of emotional processes but also to practical applications within affective computing, where accurately identifying and responding to emotional cues is increasingly essential.

Although ML techniques are often highly effective, they frequently fall short in interpretability, a key aspect for understanding the rationale behind the outcomes they produce. Interpretability refers to the degree to which a human can understand the factors influencing the decisions made by a classifier. In critical fields like medicine and healthcare research, comprehending the reasoning behind a model’s specific predictions is paramount. When an algorithm identifies a depressive state, it is particularly important to clarify the basis for this determination, providing transparency into the decision-making process. Such interpretability not only builds trust in the model’s outputs but also aids researchers in validating, refining, and ethically applying machine learning insights. To address these challenges, the field of Explainable Artificial Intelligence (XAI) has gained prominence [11]. Research in this field encompasses the development of techniques such as SHapley Additive ExPlanations (SHAP) [12] and Local Interpretable Model-Agnostic Explanations (LIME) [13], which clarify the influence of input variables on model predictions.

To study human emotions, researchers have established several models, which can generally be divided into discrete and dimensional categories. Discrete models focus on identifying specific, universally recognized basic emotions, each defined by distinct characteristics [14]. In contrast, dimensional models represent emotions along continuous scales, capturing variations in psychological and physiological attributes, such as valence and arousal [15].

Dimensional models are effective in representing the continuous spectrum of emotional states and are widely applied in research. A notable example, the Circumplex Model of Affect (CMA), arranges emotions on a two-dimensional circular plane, with arousal on the vertical axis and valence on the horizontal axis. This layout creates four quadrants: high arousal/positive valence, low arousal/positive valence, low arousal/negative valence, and high arousal/negative valence [16]. Each of these quadrants represents different emotional states based on their arousal and valence levels [17]. Fig. 1 illustrates that emotional states like depression, sadness, and boredom are associated with the quadrant characterized by low arousal/negative valence.

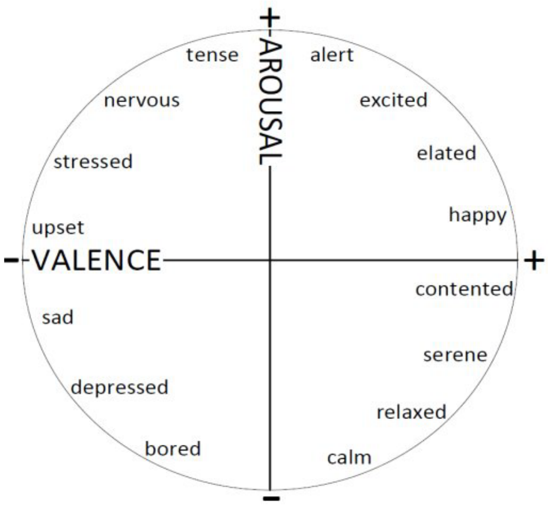

Fig. 1 The Circumplex Model of Affect [17].

By utilizing advanced Virtual Reality (VR) technologies, researchers can recreate a wide range of scenarios that elicit genuine emotional responses and behaviours [18]. This deep level of immersion created by VR offers valuable insights into human cognition and emotional states, shedding light on individuals' authentic reactions across various emotional contexts. Somarathna et al. [18] gathered data on facial expressions, heart activity, EDA, SKT, and ECG during VR games and this data was analyzed using ML techniques. The results demonstrated that VR environments effectively elicit the intended emotions. These findings highlight the significant potential of VR as an effective tool for investigating and comprehending human emotions within a controlled but dynamic environment.

This study aims to highlight the significant eye-tracking metrics that are associated with the emotional states such as depression, sadness, and boredom by leveraging the publicly available VR Eyes: Emotions Dataset (VREED) [19]. With incorporation of XAI techniques, namely SHAP, in conjunction with the emotion model of the CMA [20], we systematically assess the contributions of eye-tracking features like saccades, micro-saccades, blinks, fixations, and their interactions in understanding depressive emotional states.

II. MATERIALS AND METHOD

A. *Data Description*

This study uses the VREED (VR Eyes: Emotions Dataset), a multimodal dataset that captures emotional responses through immersive 360-degree video-based virtual environments (360-VEs) viewed via VR headsets [19]. Eye-tracking data were collected from 34 participants across 12 distinct VEs, with each set of three environments representing a quadrant of the Circumplex Model of Affect (CMA). Following a pilot phase and quality control, the final dataset includes 312 trials from 26 participants. Key eye-tracking features such as fixations, micro-saccades, saccades, and blinks were extracted, along with sub-features calculated using normalized count, mean, standard deviation, skewness, and maximum values.

The eye-tracking dataset includes a target column, ‘Quadrant Category,’ which specifies the corresponding CMA quadrant for each trial: category 0 represents High Arousal/Positive Valence, category 1 is Low Arousal/Positive Valence, category 2 is Low Arousal/Negative Valence, and category 3 indicates High Arousal/Negative Valence. The dataset consists of 312 rows and 50 columns, providing a comprehensive set of variables for analysis.

B. *Data Preprocessing*

To ensure data integrity, missing values were first imputed with the column averages. We then applied Principal Component Analysis (PCA) for dimensionality reduction, which both alleviates the curse of dimensionality and reveals the data's underlying structure by transforming original features into orthogonal components. Using PCA, we generated new features by grouping fixations, blinks, saccades, and micro-saccades. This process resulted in 15 features, including: Number of Micro-Saccade, Number of Blink, Number of Saccade, Number of Fixations, Blink Duration, Fixation Duration, Saccade Duration, Saccade Direction, Saccade Amplitude, Saccade Length, Micro-Saccade Amplitude, Micro Saccade Direction, Micro Saccade Peak Velocity, Micro Saccade Vertical Amplitude, and Micro Saccade Horizontal Amplitude.

To analyze quadrant 2, we reformatted the ‘Quadrant Category’ target column, initially containing four distinct values, into a binary classification format for each category. This restructuring introduced an imbalance, with category 0 comprising only 78 trials and the remaining categories accounting for 234 out of 312 trials. To tackle this issue, we applied the Synthetic Minority Over-sampling Technique (SMOTE) [20], which successfully balanced the dataset by increasing the representation of minority classes. Following SMOTE, we obtained a balanced dataset ideal for unbiased binary classification.

C. *Machine Learning Model Selection*

In this study, the Extra Trees Classifier (ET) was selected as our predictive model due to its superior performance across various metrics, specifically the F1-score, as it provides a more robust evaluation with imbalanced data. Selecting a model with strong predictive performance is essential to ensure the reliability of XAI techniques, such as SHAP. This method seeks to accurately convey the importance and impact of each feature on the model’s predictions. If a low-performing model is used, it could lead to misleading interpretations, as the SHAP values would reflect an inaccurate portrayal of the model's behaviour.

D. *SHAP For Model Interpretation*

After developing a ML model to serve as the basis for our analysis, we concentrated on incorporating XAI techniques to improve model interpretability. We used the SHAP library in Python to calculate SHAP values for the features in our dataset. The SHAP framework assigns a SHAP value to each feature, measuring its individual contribution to the model’s prediction for a particular instance. Originally derived from cooperative game theory, where SHAP values ensure a fair distribution of benefits among players, these values are adapted within the SHAP framework to apportion the model’s output among features according to their relative contributions.

Our analysis focused on evaluating the relative importance of features within the dataset across the individual CMA quadrant category 2 which is associated with depression, sadness, and boredom. By applying the SHAP algorithm to our model, we aimed to uncover which eye-tracking features are most influential in eliciting emotions such depression, sadness, and boredom.

III. RESULTS

After the application of the ML model on the dataset, we employed the SHAP algorithm to generate visual representations of the influence exerted by these eye-tracking metrics for Quadrant 2 of the CMA. These influences are depicted in the summary plot shown in Figure 2.

The y-axis displays the feature names, with the most impactful feature at the and the least impactful at the bottom. The x-axis represents the SHAP value, which indicates the impact of each feature on the model output. A positive SHAP value means the feature increases the model’s output for this class, while a negative SHAP value means it decreases it. The further a point is from 0, the greater its impact. Each dot represents a sample in the test set, and the colour indicates the feature’s actual value for that sample, blue for low values to red for high values.

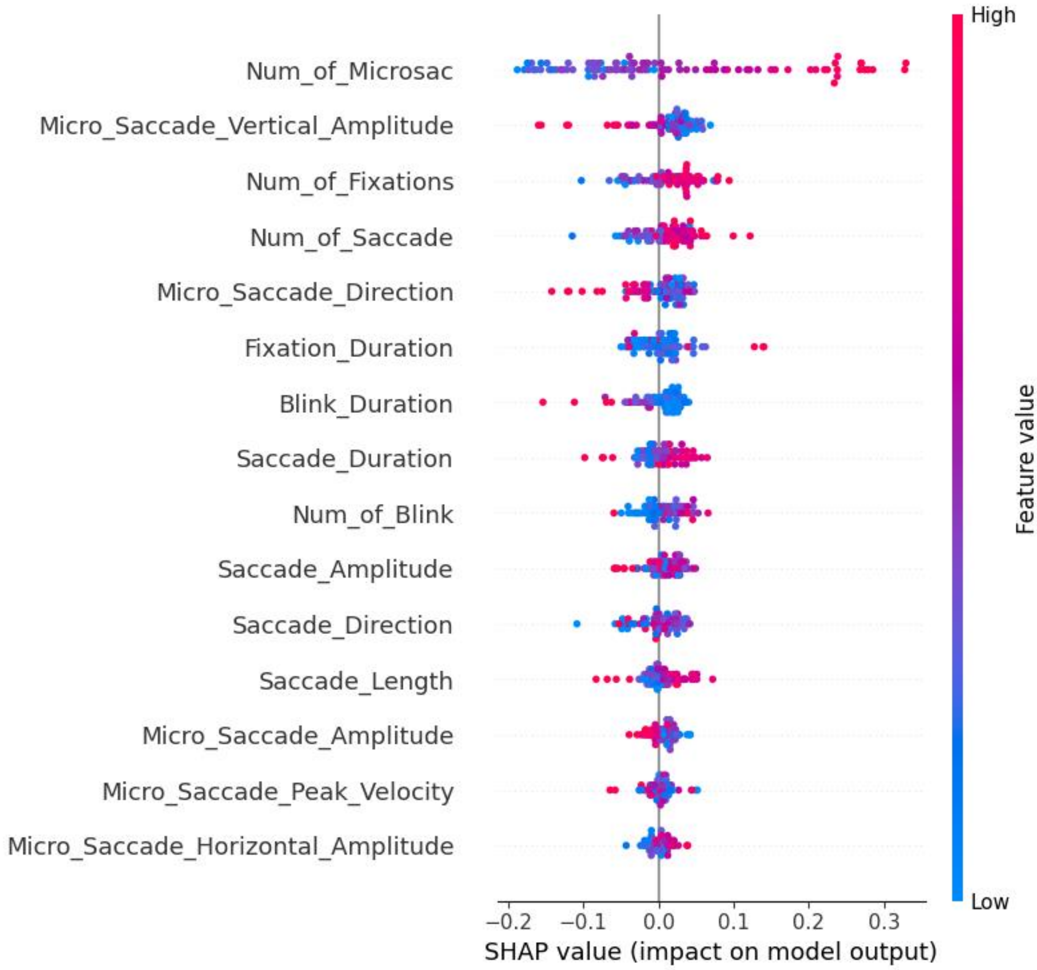

Fig. 2 Summary plot of the results

Table 2. Impacts of the features on model output

Feature	Impact on the model
Number of Micro-Saccade	Higher values positively impact
Micro-Saccade Vertical Amplitude	Lower values positively impact
Number of Fixations	Higher values positively impact
Number of Saccade	Higher values positively impact
Micro-Saccade Direction	Higher values positively impact
Fixation Duration	Neutral or higher values positively impact
Blink Duration	Lower values positively impact
Saccade Duration	Higher values positively impact
Number of Blink	Higher values positively impact
Saccade Amplitude	Neutral, lower values may impact positively
Saccade Direction	Neutral, higher values may impact both positive and negative
Saccade Length	Higher values influence both positive and negative
Micro-Saccade Amplitude	Lower values positively impact
Micro-Saccade Peak Velocity	Some high values negatively impact but generally neutral impact
Micro-Saccade Horizontal Amplitude	Higher values positively impact

The most impactful feature identified is the ‘Number of Micro-Saccade’, with higher values being significant predictors for depressive or negative affective states. This suggests that increased frequency of small, involuntary eye movements (micro-saccades) during visual fixation is associated with sadness, depression, or boredom. In contrast, the results show that lower values of ‘Micro-Saccade Vertical Amplitude’ and ‘Micro-Saccade Amplitude’ are also positively related to predictions, indicating that smaller vertical angular movements are characteristic of depressive states. Interestingly, larger values of ‘Micro-Saccade Horizontal Amplitude’ tend to yield higher SHAP values, implying that larger horizontal micro-saccadic movements also play a role in these emotional contexts. Further observations reveal that lower values of ‘Micro-Saccade Direction’ positively impact model predictions. This could indicate that a specific orientation or predominant path of micro-saccades is related to depressive emotions. The ‘Number of Fixations’ also stands out as a significant feature, positively influencing the model. While ‘Fixation Duration’ has a mostly neutral impact, it exerts a positive influence at higher values. Saccadic eye movements such as ‘Number of Saccade’, ‘Saccade Duration’, and ‘Saccade Length’ positively influence predictions when values are higher. However, blink movements show nuanced insights. Lower values of ‘Blink Duration’ positively affect predictions, suggesting that individuals with depression or sadness may blink less frequently, while a reduction in the ‘Number of Blink’ has a negative impact on the model.

IV. DISCUSSION

The findings provide insightful interpretations of eye-tracking metrics in relation to emotional states such as sadness, depression, and boredom. These results highlight the relevance of specific eye-movement characteristics, shedding light on how certain patterns are more prevalent in individuals experiencing these emotions.

Our results on fixation metrics correlate with the literature. ‘Number of Fixations’ and ‘Fixation Duration’ emerge as significant features, positively impacting the model. This suggests that individuals experiencing sadness or depression tend to have more frequent fixations and for longer durations. This aligns with findings indicating that frequent fixations may reflect lower cognitive engagement or attentiveness, often seen in depressive states. On the other hand, depressed individuals, often experience reduced motivation to explore due to feelings of loss of interest or pleasure. Consequently, they may fixate for longer periods rather than actively scanning their environment. However, due to reduced cognitive flexibility depressive individuals may also show prolonged fixations.

Saccadic eye movements reveal complex patterns in existing research. Our results show that a higher ‘Number of Saccade’, ‘Saccade Duration’, ‘Saccade Amplitude’, and ‘Saccade Length’ are predictors of depressive states, contrasting earlier findings suggesting that depressed individuals exhibit fewer saccades. Longer saccade durations may be linked to reduced environmental engagement, typical in individuals experiencing depressive or negative emotions. This may reflect a broader scanning or exploratory behaviour in the visual field.

The most impactful feature identified is the ‘Number of Micro-Saccade’, with higher values being significant predictors for depressive or negative affective states. This indicates that a higher frequency of small, involuntary eye movements (micro-saccades) during visual fixation is linked to feelings of sadness, depression, or boredom. As a result, micro-saccades could be a useful indicator for identifying these emotional states, consistent with the heightened sensitivity to negative stimuli and attentional difficulties often seen in individuals with depression. Conversely, the results reveal that lower values of 'Micro-Saccade Vertical Amplitude' and 'Micro-Saccade Amplitude' are positively associated with predictions, suggesting that smaller vertical eye movements are indicative of depressive states. Interestingly, larger 'Micro-Saccade Horizontal Amplitude' values correspond with higher SHAP values, indicating that more pronounced horizontal micro-saccadic movements are also relevant in these emotional contexts. These findings suggest that while overall micro-saccadic activity may rise with depressive states, the specific amplitude and direction of these movements provide additional meaningful insights.

V. CONCLUSION

This study demonstrates that eye-tracking metrics are valuable for detecting depressive emotional states within virtual reality environments, emphasizing the roles of micro-saccades, fixation frequency, and saccadic behaviour. The integration of XAI allowed for an interpretable model, clarifying the importance of each feature in predicting depressive states. These findings contribute to the growing field of affective computing, enhancing our understanding of the visual patterns associated with depressive emotional states. Future work could expand on these insights by investigating additional eye-tracking parameters and validating the approach across different affective disorders and VR settings.

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